Social networks and information silos influence conservation knowledge in tourist populations

Hannah Henry[1], TiAnna Olivas[1], Kelsey McCune[1], Kelly H. Dunning[2], Janna R. Willoughby[1,*]

1. College of Forestry, Wildlife, and Environment, Auburn University, Auburn, Alabama
2. Haub School of Environment and Natural Resources, University of Wyoming, Laramie, Wyoming

*jwilloughby@auburn.edu

Marine tourism is a rapidly expanding industry with significant impacts on marine ecosystems and species. The behavior of individuals engaging with these ecosystems for economic or recreational purposes plays a strong role in the success of conservation efforts. To mitigate some of the negative effects human actions can have on ecosystems, effective dissemination of conservation knowledge and policies is required. This study used an agent-based model to explore how social interactions and information silos within and between local and tourist populations influenced social learning about conservation knowledge. Specifically, we examined how demographic group size and interaction frequency among locals and tourists in marine tourism settings influence conservation knowledge dissemination. Our results revealed that both the frequency of interactions and the relative sizes of demographic groups significantly affected knowledge accumulation among tourists. In general, higher interaction probabilities led to more social learning, particularly among well connected and large groups. However, reduced interaction probabilities between certain demographic groups acted as information silos, which resulted in lower knowledge levels in these groups, although this could be mitigated by increased educational efforts. These findings suggest that while increasing interaction opportunities is important, the context and structure of these interactions are equally important. Tailoring educational interventions to the specific dynamics of group-identity based social interactions in marine tourism can enhance the effectiveness of conservation efforts and optimize outcomes for wildlife protection.

Keywords: agent-based model, conservation knowledge, information silos, social learning, tourism

Introduction

Marine tourism is a significant and rapidly expanding sector of the global tourism industry, projected to constitute the largest share (26%) of the global ocean economy by 2030 and employing approximately 8.6 million people (Dwyer, 2018). This growth brings substantial economic, cultural, and environmental impacts, and presents unique opportunities and challenges for marine wildlife conservation (Miller, 1993; M. Orams, 1998). Marine tourism can incentivize managing authorities and stakeholders to protect natural areas due to the economic and social benefits of tourism while also promoting public education about these ecosystems (Burger, 2000; Cheung & Fok, 2014; Salm, 1985; Scheyvens, 1999; Zeppel & Muloin, 2008). Concurrently, the behavior of tourists and tourism operators can also lead to negative effects on the marine environment and the diverse species that inhabit them, such as habitat loss, degradation, pollution, and wildlife disturbance (Badalamenti et al., 2000; Hardiman & Burgin, 2010; Harriott, 2004). Their behaviors—such as adhering to wildlife interaction guidelines, properly disposing of waste to prevent pollution, and following regulations to avoid damaging sensitive habitats—play a pivotal role in either supporting or undermining collective efforts to protect wildlife from anthropogenic impacts (Bisack & Clay, 2020; Fabian et al., 2020; O'Bryhim &

Parsons, 2015). As a result, the effectiveness of conservation efforts in marine tourism contexts largely depends on the dissemination of relevant conservation knowledge to diverse audiences, particularly tourists.

Social learning, defined as knowledge transmitted from informed to naïve individuals that leads to changes to socio-ecological systems (Reed et al., 2010), can increase the uptake of conservation knowledge and practices by local communities (Rist et al., 2007; Toderi et al., 2007), as well as tourists (Medio et al., 1997; M. B. Orams & Hill, 1998). Local communities often act as the custodians of local ecological knowledge, drawing on long-standing relationships with the natural environment that are important to inform conservation practices (Gilchrist et al., 2005; Mallory et al., 2006; Olsson & Folke, 2001). Additionally, these communities frequently serve as one of the first points of contact for tourists, offering guidance, education, and cultural perspectives that can influence tourist behavior, and consequently, conservation outcomes (Keane et al., 2011; Masud et al., 2017). However, the extent to which these interactions facilitate the effective transmission, and therefore learning, of conservation knowledge depends on their structure and the frequency in which they occur (De Souza et al., 2022; Lück, 2015; Sterling et al., 2017).

Existing research concerning social learning interventions for increasing conservation knowledge has primarily focused on defining social learning (Reed et al., 2010) and testing the efficacy in structured educational encounters. This can include guided eco-tours led by conservation organizations, marine wildlife observation programs, educational boat trips in coastal areas, and hands-on conservation activities like coral reef restoration, beach clean-ups, or citizen science projects coordinated by non-governmental organizations and ecotourism operators (Ballantyne et al., 2011; Jacobson & Robles, 1992; Kleespies et al., 2022; Lee et al., 2023; M. B. Orams, 1997). While these approaches may be effective in certain contexts, they often overlook the role of informal or incidental educational encounters—such as conversations and community events exchanges—which are frequently employed in public engagement campaigns by state fish and wildlife organizations (Rossing, 1991; Watkins & Marsick, 1992). In many marine tourism contexts, informal social interactions that encompass both local and tourist populations play a fundamental role in shaping the flow of information, ultimately influencing how communities interact with their environment and manage natural resources (Allen et al., 2001). These social networks are characterized by varying degrees of connectivity, frequency of interactions, and trust among members, which can influence the spread of information (Adams, 1967; Sherchan et al., 2013; Wang & Wellman, 2010). Within these networks, conservation knowledge diffuses with varying efficiency and longevity based on the structure and frequency of social interactions (Boyd et al., 2011). Additionally, variations in the content and method of information dissemination across different local groups often reflect underlying social, cultural, and economic dynamics (Davtian et al., 2022). These variations influence how information is received and acted upon, presenting potential barriers and facilitators to effective conservation messaging (Ma et al., 2022). For example, information silos —social structures in which information is shared within subgroups but not across them—can hinder the spread of conservation messaging and lead to disparities in knowledge across different segments of the local population (Rogers, 2003). These silos may arise due to demographic differences, cultural divides, language barriers, or geographic isolation (Mixon, 2008; Pino, 2023).

In marine tourism settings, the rapid dissemination of accurate and impactful conservation information—such as wildlife ecology, sustainable practices, and legal regulations—is essential for fostering consistent environmental behaviors among both locals and tourists. Social learning theory provides a useful framework for understanding the broad patterns of information dissemination, although the specific mechanisms governing how knowledge is shared, retained, or lost within marine tourism remain inadequately explored. When communication silos exist, they can result in fragmented knowledge, leading to inconsistent or even harmful practices that undermine conservation efforts (Bento et al., 2020). Addressing these communication gaps is critical for ensuring that all stakeholders are not only well-informed but also actively engaged in sustainable actions, ultimately improving the resilience of marine ecosystems and the long-term sustainability of tourism. Recent studies have highlighted the importance of social network structures in shaping human behavior and information diffusion in natural resource governance contexts (Bodin & Crona, 2009; Prell et al., 2010). Yet, few studies have explicitly examined how these dynamics influence conservation knowledge and behaviors among tourists and local communities in marine environments. There is a need to explore how factors such as group size, frequency of interactions, and group demographic identities affect the accumulation and dissemination of conservation knowledge.

To address this gap, this study employs an agent-based modeling (ABM) approach to explore critical aspects of social interactions in marine tourism settings, focusing on the effects of information silos in information disparity among groups. ABM are particularly well-suited for studying complex social systems because it allows for the simulation of individual behaviors and interactions within a networked environment, capturing the emergent properties of the system as a whole (Railsback & Grimm, 2019). In our model, we specifically considered the relative effects of group size and information sharing frequency on total knowledge within groups as well as the ways in which the structure of local social interactions influence knowledge and information sharing. We modeled both structured interactions, such as organized educational programs, and incidental encounters, such as casual conversations, to understand the impact on uptake of conservation knowledge. Our analysis aimed to identify the conditions under which knowledge dissemination was most effective and to propose strategies for enhancing the reach and impact of conservation messaging in marine tourism settings relevant for both practitioners and policymakers.

Methods

Model overview

Our agent-based model simulated the dynamics of knowledge transfer and behavioral changes within populations of locals and tourists in marine tourism settings and focused on how social interactions and targeted interventions impact conservation efforts. The model included two main types of agents —locals and tourists —which were further divided into three demographic groups. Each agent was characterized by their demographic group, knowledge level, and agent type (local or tourist). The model was informed by key theoretical frameworks, including social learning theory, behavior change theory, and memory decay (Ajzen, 1991; Bandura, 1977). In social learning theory the probability of knowledge transfer between individuals is greater with increased interaction frequencies between locals and tourists. Conversely, the presence of information silos acted as a barrier to social learning, reducing the spread of conservation knowledge across isolated demographic groups. Randomness was incorporated in the selection of interaction partners, the outcomes of knowledge transfer, and the processes of learning new information and forgetting existing information. The simulation operated on an annual time scale, with each run modeling knowledge accumulation and loss over a 25-year period. Ultimately, simulated output that described interaction outcomes and knowledge were collected for each year of each run and analyzed to assess the effectiveness in learning and knowledge transfer relevant to encouraging conservation behavior changes. Expected emergent behaviors included patterns of knowledge dissemination across demographic groups and changes in conservation-related behaviors driven by interactions and educational inputs. Table 1 summarizes the key parameters used in the agent-based model, outlining their definitions, value ranges, and roles in simulating knowledge dissemination dynamics among demographic groups.

Table 1. Parameters of the agent-based model used to simulate knowledge transfer and information silos in marine tourism settings.

Parameter	*Description*	*Values/Range*	*Purpose in Model*
Group Size	The proportion of the total population assigned to each demographic group.	Group 1: 50%, Group 2: 25%, Group 3: 25%	Defines demographic distribution within the agent population.
Interaction Probability	The probability that an interaction occurs between individuals within and across demographic groups.	0.0 - 1.0 (in intervals of 0.1)	Controls frequency of social interactions, influencing knowledge dissemination.
Knowledge Level	The initial knowledge level of each agent represents conservation knowledge. It is adjusted annually based on interactions, education, and memory decay.	Continuous variable from 0 to 1	Serves as a dynamic baseline state variable modified by other parameters.
Knowledge Transfer Probability	The probability that an agent successfully transfers knowledge during an interaction.	0.0 - 1.0	Represents the likelihood of knowledge exchange in interactions.
Knowledge Gain (Interactions)	The amount of knowledge transferred during a successful interaction, determined by the transmitting agent's knowledge level.	Normally distributed (mean = transmitting agent’s knowledge, SD = 0.1)	Models the variability in knowledge gained from each successful interaction, simulating real-world differences in learning.
Knowledge Gain (Educational Intervention)	Incremental knowledge gain due to targeted	Normal distribution (mean =	Simulates the cumulative effect of

	educational interventions per agent per year.	educational content value per group, SD = 0.1)	conservation education on knowledge acquisition, with variability across groups and scenarios.
Forget Rate	Probability of knowledge loss due to memory decay over time.	0.0 - 0.2	Models potential knowledge loss, reflecting real-world forgetting.

Model details

The agents in the model represent individuals from three demographic groups, with Group 1 comprising 50% of the total population and Groups 2 and 3 each representing 25%. This distinction allows us to explore how varying group sizes impact knowledge transfer, as larger groups may facilitate more interactions and thus have a different potential for knowledge dissemination than smaller groups. Each agent was assigned an initial knowledge level, represented as a continuous variable that ranged from 0 (no knowledge of the ecosystem or laws) to 1 (perfect knowledge of an ecosystem or laws). This state variable could be modified by education, stochastic loss of knowledge between model time points, and transmission of knowledge from one individual to another. Agents passed knowledge through informal means, where information was transferred based on the combination of interaction probabilities and knowledge transfer effectiveness. This was further modified by targeted educational interventions that increased knowledge among particular segments of the local and tourist populations (combinations of these described below).

Interactions between individuals were structured within and between demographic groups, with probabilities influencing the likelihood and impact of these encounters on knowledge transfer.

Across all model runs, this interaction probability varied between 0 and 1 at an interval of 0.1, and this parameter was set for the entire population of locals and tourists combined. For some model scenarios, the interaction probability parameter value was modified by an adjustment term to understand how interaction probability influenced knowledge accumulation over time. The interaction adjustment worked by reducing the probability of interactions occurring in one group proportionally to another group's interactions. Individuals' interactions were determined for each pairwise combination of potential interactions annually: interactions between tourists and locals that were assigned the same demographic group, interactions among tourists irrespective of assigned demographic group, interactions among locals that were assigned the same demographic group, and interactions among locals irrespective of assigned demographic group. Ultimately, an individual's interaction or lack of interaction at each opportunity was determined by a random deviate from a binomial distribution, where the probability of interacting (potentially modified by the interaction adjustment parameter) was the probability of a 1 in the binomial distribution.

Social learning between individuals occurred within and among individuals assigned to each of the three demographic groups as well as among individuals that were tourists and locals. Knowledge transfer between individuals occurred through a two-step process. First, an agent must have been selected to interact based on the global interaction probability. Then, if selected, the agent attempted to transfer knowledge to its interaction partner. Whether the partner learned was probabilistic and modeled using a binomial distribution. A successful interaction increased the partner's knowledge, with the amount of knowledge gained determined by a continuous variable drawn as a random deviate from a normal distribution with a mean equaling the transmitting agent's knowledge and a standard deviation of 0.1. This probabilistic framework was designed to reflect real-world variability in social learning during interactions, where ideas and behaviors diffuse with varying degrees of success based on interaction dynamics and individual differences.

We incorporated learning opportunities within the model to simulate how targeted educational interventions influenced knowledge acquisition among tourists. The learning function operated by providing chances for knowledge increases across all three demographic groups. Each agent's knowledge was adjusted by an amount drawn from a normal distribution, where the mean corresponded to the educational content value assigned to the demographic group and the specific simulation scenario, with a standard deviation of 0.1. This approach introduced variability, reflecting the reality that individuals within the same demographic group may have absorbed and retained knowledge differently. Knowledge values were bounded by 0 (indicating no knowledge) and 1 (indicating perfect knowledge), with any values falling below 0 set to 0 and those above 1 set to 1. This process was repeated annually, simulating the cumulative impact of education on knowledge dissemination throughout the simulation period.

We also included the opportunity for the loss of knowledge for individuals over time. For each individual, the likelihood of forgetting was modeled as a binary outcome using a binomial distribution, where the probability of forgetting was determined by the `forget` parameter. For those agents who were selected to forget, the amount of knowledge lost was drawn from a normal distribution with a mean set by a forget quantity parameter and a standard deviation of 0.1. As with the learning function, knowledge was bound by 0 and 1 such that any negative values generated during this process were corrected to zero before updating the population. This process was repeated annually, simulating the potential erosion of knowledge over time.

Model analysis

At the end of each simulation year, we used three outcome metrics to assess the effectiveness of knowledge dissemination and behavior change in response to interactions and educational interventions. Specifically, we measured 1) the average knowledge levels for each demographic group, 2) the variance in knowledge across groups and agent types, and 3) the effects of educational interventions and spontaneous interactions on knowledge gains. For each simulation run, we recorded these outcome metrics annually and across all agents, distinguishing between the six subgroups (three demographic groups for both locals and tourists). These values were then summarized over 100 replicates for each parameter set to ensure robustness and account for variability in the simulation results.

To evaluate statistical significance, we compared the average knowledge levels between demographic groups and agent types using 95% confidence intervals (mean ± 1.96 * standard error). This allowed us to detect significant differences in knowledge accumulation across groups and to determine whether the interactions or educational interventions had a meaningful impact on knowledge levels. To determine the variance explained by interactions, we used a linear regression where interaction probability was the predictor variable and mean population knowledge was the response variable, and each demographic group was modeled independently. We also compared the effects of knowledge transfer on mean population knowledge using a linear model where the knowledge transfer was first logged and then used as the predictor variable. All analyses were carried out in R (R Core Team, 2023), and all code was archived and available via a dedicated GitHub repository (https://github.com/jwillou/socialdata).

Results

Our model focused on understanding social interactions in marine tourism settings, with a focus on the effects of information silos in social learning disparity among groups. Through our modeling effort, we considered the effects of these disparities among and within various demographic groups to understand how education and information sharing can be designed and encouraged to benefit conservation outcomes. Overall, we found that the effectiveness of knowledge transfer was influenced by both the frequency of interactions between locals and tourists and the relative sizes of the demographic groups involved. The probability of interaction between locals and tourists played a significant role in shaping social learning within the tourist groups (Figure 1). In our model, higher interaction probabilities were associated with greater knowledge accumulation among tourists, irrespective of population size; in all groups, knowledge was significantly related to interaction probability, with R^2 values near one for all three demographic groups (Table 2). In addition, when the interaction probability was reduced by 50% in one of the smaller demographic groups, the mean knowledge after 25 years was higher than expected compared to the other small group with more frequent interactions, with only an average of 43% reduction in knowledge across interaction probabilities (Figure 1). This suggests that the group with fewer interactions may have benefited from more focused or efficient knowledge transfer compared to the situation where groups interact frequently but do not have new information to share.

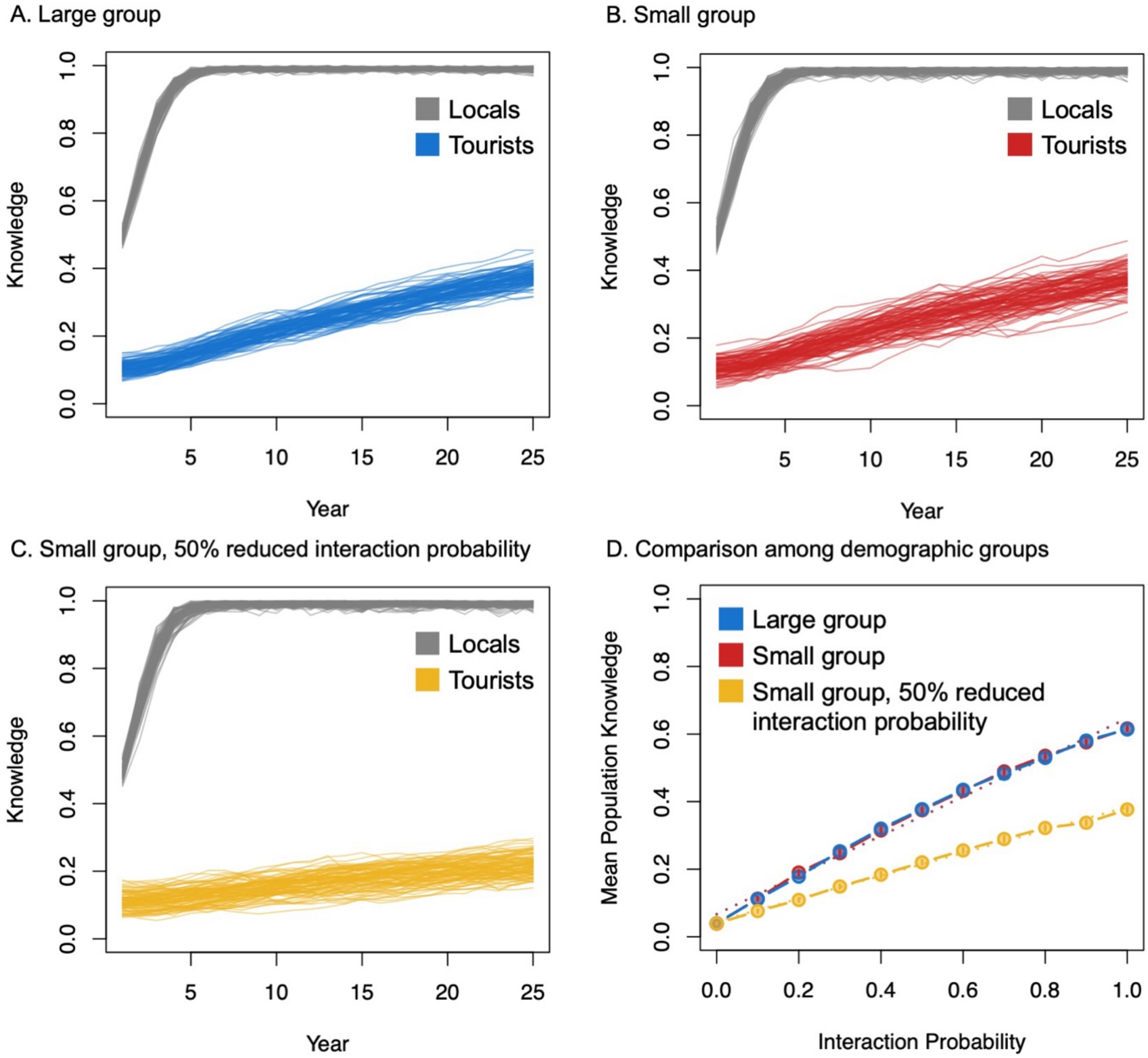

Figure 1. Mean knowledge within each tourist demographic group when education targeted locals and information passed from locals to tourists via interaction among these groups. Knowledge of tourists in the large demographic group (A, 50% of all simulated individuals) increased through interaction with locals at the same rate as knowledge in one of the smaller-sized demographic groups (B, 25% of all simulated individuals), where tourists in both groups had a 50% chance of interacting with locals. Tourists in the second smaller-sized demographic group (C, 25% of all simulated individuals) had only a 25% chance to interact and learn from locals compared to the other small demographic group and the large demographic group. This pattern persisted over other interaction probabilities (categorized by the unpenalized interaction probability, D). In these scenarios, knowledge transfer was limited to 5% of the total knowledge for an individual for each interaction where knowledge transfer occurred. Regression lines comparing interaction probability to mean knowledge after 25 years illustrated by dotted lines.

Table 2. Linear regression results predicting interaction probability between demographic groups on mean population knowledge after 25 years of interactions. Intercept and slope coefficients (coef.), standard error (SE), and p-values as well as the F-statistic (F), R^2, and degrees of freedom (DF) are indicated for each of the three models.

Population	**Intercept Coef. (SE), p-value**	**Slope Coef. (SE), p-value**	**F**	**R^2**	**DF**
Large demographic group	0.03 (0.01), 0.003	0.56 (0.01), <0.001	1950	0.99	1 and 9
Small demographic group	0.03 (0.01), 0.001	0.56 (0.01), <0.001	1735	0.99	1 and 9
Small demographic group with 50% reduced interaction probability	0.01 (0.00), 0.001	0.32 (0.01), <0.001	3725	0.99	1 and 9

The quantity of information transferred during each interaction also significantly impacted the overall knowledge levels within the groups. Across all interaction probabilities we compared the effects of altered knowledge transfer quantity in large (Figure 2A) and small (Figure 2B) demographic groups and found that different group sizes did not result in any significant difference in mean group knowledge after 25 years, across all interaction probability and knowledge quantity transfer pairs (Figure 2D). When the interaction probability for one group was reduced by 50% relative to the whole population (Figure 2C), mean knowledge in year 25 was also reduced (Figure 2D). Across all populations and knowledge transfer quantities, the relationship between interaction probability and mean population knowledge at year 25 plateaued as mean knowledge approached higher levels (0.9 and above), suggesting diminishing returns from additional knowledge transfer as groups became information saturated. Comparing between the small size groups where one group passed information approximately 50% less than the other group, the proportion of mean knowledge compared between these two groups scaled with knowledge transmission (Figure 3; intercept=1.09, slope=0.19, p-value=<0.001, R^2=0.99, DF= 1 and 8). Even when knowledge transfer quantity was low to moderate (i.e. <0.2), the proportion of knowledge in the group interacting half as much was still 51-77% of the knowledge in the other group, and these two groups converged as knowledge transmission increased (Figure 3).

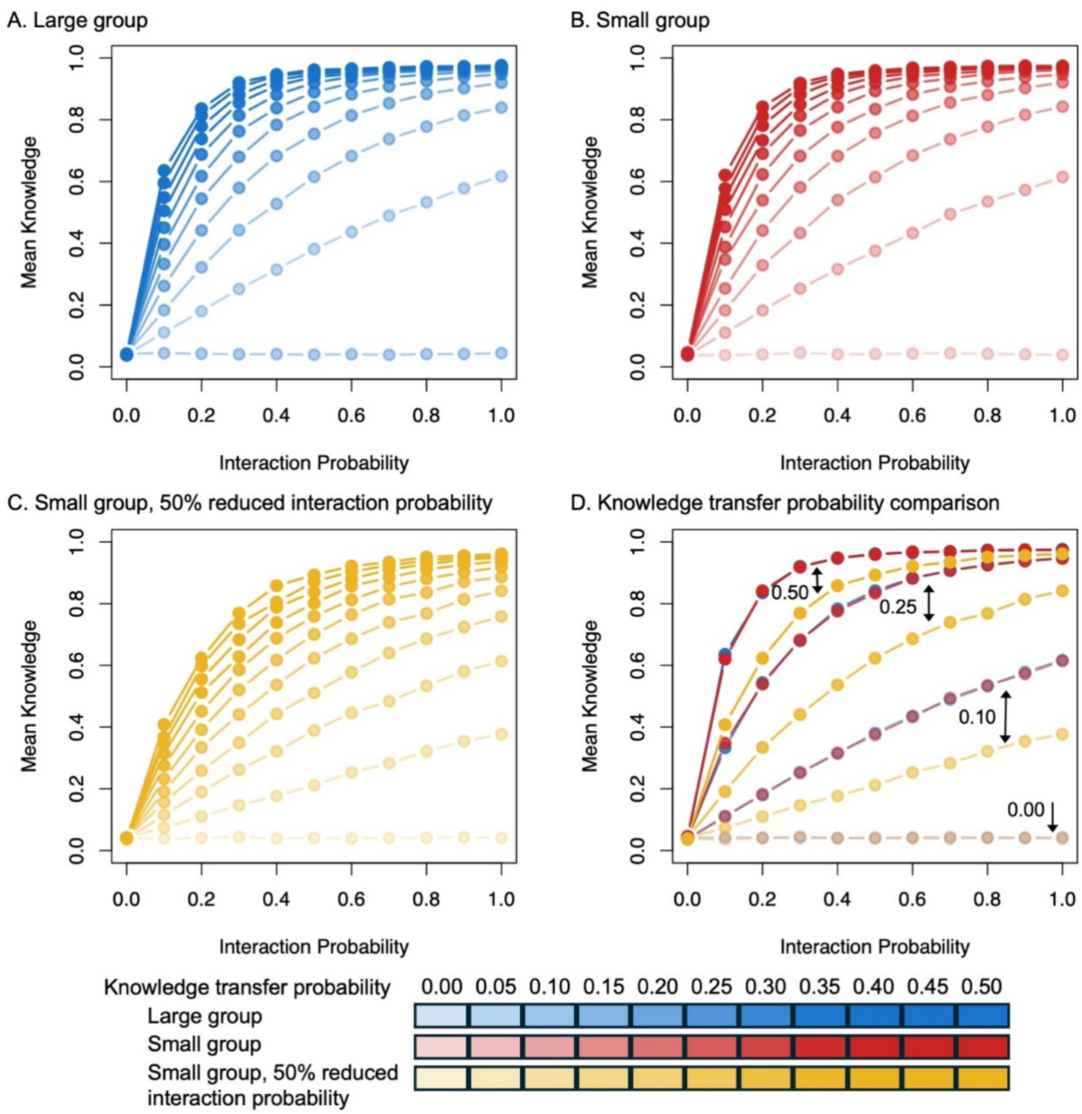

Figure 2. Effects of the quantity of information passed between individuals on the mean knowledge of individuals in each group after 25 years of interactions. Across the large populations (A) and smaller populations (B and C), increasing transmission of knowledge that happened when individuals interacted (depicted by increasing color saturation in each plot), resulted in faster rates of increase in mean tourist knowledge for each group. This exponential increase plateaued as populations neared information saturation. When the probability of successfully communicating information between individuals was reduced by half (panel C compared to B, illustrated in D), this decreased the magnitude of this effect (offsetting increases

along the x-axis), but the overall pattern of mean knowledge increase remained the same. In panel D, selected knowledge transfer amount values are depicted and noted to illustrate this pattern.

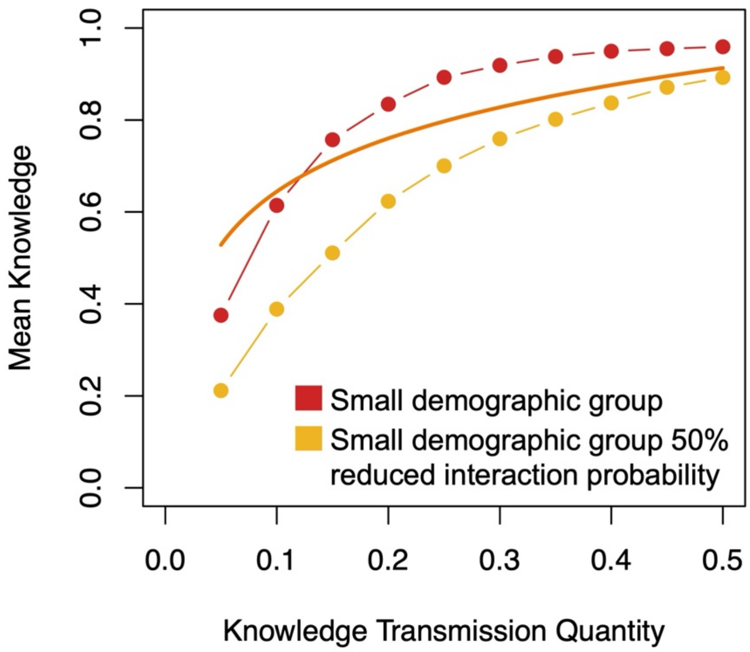

Figure 3. Knowledge transfer quantity effects on mean tourist knowledge when knowledge transfer probability is altered. Solid orange line shows regression between knowledge transmission (logged for the regression and back calculated here for plotting) and the proportion of mean knowledge in the reduced interaction probability population (yellow) relative to the standard interaction probability population (red). When knowledge transfer quantity was low to moderate (i.e. <0.2), the proportion of knowledge in the group interacting half as much was still 51-77% of the knowledge in the other group.

We also considered how education efforts that targeted both tourists and locals interacted with demographic group size to understand the influence on mean knowledge in these populations. In all scenarios, group size did not result in any significant effect on mean population knowledge after 25 years of educational efforts (Figure 4), and mean knowledge was generally significantly positively related to interaction probability of each scenario (Table 3). When education targeted locals only, we found lower mean knowledge after 25 years in the demographic group with the 50% reduced interaction probability compared to the other groups. The regression coefficients were smaller, illustrating reduced effectiveness of these interactions (Figure 4 A, C, E).

Conversely, there was no significant difference between these groups when education targeted locals and tourists as evidenced by the typically overlapping confidence intervals around the mean tourist group knowledge after 25 years of education (Figure 4 B, D, F) and the similar regression coefficients among these groups (Table 3).

We also considered how education efforts that targeted both tourists and locals interacted with educational knowledge gain and stochastic knowledge loss quantity to understand the influence on mean knowledge in these populations. As expected, when education content was relatively large and knowledge loss due to forgetting was small, mean knowledge in tourist groups was the highest (Figure 4 A and B), particularly when education content targeted both locals and the tourists themselves (Figure 4 B). Disparities in mean tourist group knowledge persisted when demographic groups had reduced interaction probabilities with other individuals and groups across all education and knowledge loss values considered when education targeted locals only (Figure 4 A, C, E). However, this disparity among demographic groups was lost when education targets include tourists, even when the stochastic knowledge loss parameter was larger than the education knowledge gain parameter (Figure 4 F). This was due to the increased knowledge sharing that increased mean knowledge values for many individuals in all demographic groups even if some members of the groups ultimately lost this information.

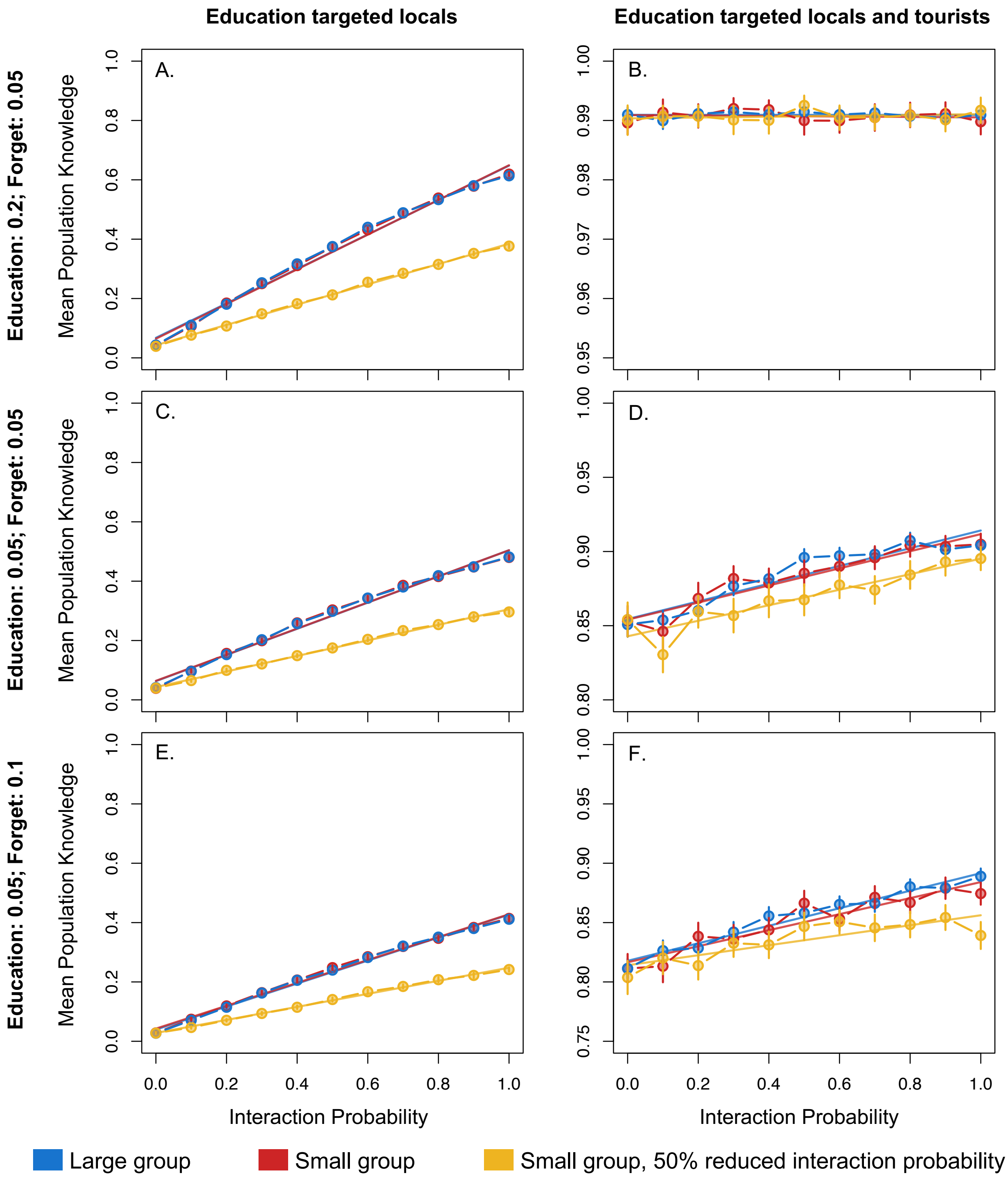

Figure 4. Comparison of mean knowledge among three demographic groups of tourists when education targets were varied between targeting locals only and targeting locals as well as tourists (bolded labels along top of plot), over varied effectiveness of educational content and stochastic knowledge loss (bolded labels along left side of plot) and interaction probabilities among individuals (x-axis). Regression lines between interaction probability and mean knowledge of tourists in each group is indicated by the dotted line. Mean knowledge of the group, averaged over 100 replicates, is indicated by the circles, and 1.96*standard error around

these means is indicated by the error bars. When education targets locals only (A, C, E), reduced interaction probability of one group limits educational gains and overall mean education in tourists is low. When education targets locals and tourists (B, D, F), mean tourist knowledge increases significantly for all demographic groups, even when one group interacts less often than the others. This is true even when stochastic knowledge loss is greater than knowledge gained from education (F). Note the y-axis ranges in panels B, D, and F.

Table 3. Linear regression results predicting interaction probability between demographic groups on mean population knowledge after 25 years of interactions when education efforts targeted locals and tourists. Intercept and slope coefficients (coef.), standard error (SE), and p-values as well as the F-statistic (F), R^2, and degrees of freedom (DF) are indicated for each of the three models run under each education and knowledge loss scenario.

Population	**Intercept Coef. (SE), p-value**	**Slope Coef. (SE), p-value**	**F**	**R2**	**DF**
Education gain 0.2 targeting locals, forget 0.05					
Large demographic group	0.07 (0.01), <0.001	0.58 (0.02), <0.001	909	0.99	1 and 9
Small demographic group	0.06 (0.01), <0.001	0.58 (0.02), <0.001	1170	0.99	1 and 9
Small demographic group with 50% reduced interaction probability	0.04 (0.00), <0.001	0.34 (0.00), <0.001	6543	0.99	1 and 9
Education gain 0.2 targeting locals and tourists, forget 0.05					
Large demographic group	0.99 (0.00), <0.001	0 (0.00), 0.99	9.27	1.00	1 and 9
Small demographic group	0.99 (0.00), <0.001	0 (0.00), 0.65	0.22	0.02	1 and 9
Small demographic group with 50% reduced interaction probability	0.99 (0.00), <0.001	0 (0.00), 0.38	0.87	0.09	1 and 9
Education gain 0.05 targeting locals, forget 0.05					
Large demographic group	0.06 (0.01), <0.001	0.44 (0.01), <0.001	896	0.99	1 and 9
Small demographic group	0.06 (0.01), <0.001	0.44 (0.02), <0.001	724	0.99	1 and 9
Small demographic group with 50% reduced interaction probability	0.04 (0.00), <0.001	0.26 (0.01), <0.001	3615	0.99	1 and 9
Education gain 0.05 targeting locals and tourists, forget 0.05					
Large demographic group	0.85 (0.00), <0.001	0.06 (0.01), <0.001	72.7	0.89	1 and 9
Small demographic group	0.85 (0.00), <0.001	0.06 (0.01), <0.001	85.2	0.9	1 and 9
Small demographic group with 50% reduced interaction probability	0.84 (0.00), <0.001	0.05 (0.01), <0.001	50.3	0.85	1 and 9
Education gain 0.05 targeting locals, forget 0.1					
Large demographic group	0.04 (0.00), <0.001	0.39 (0.01), <0.001	1567	0.99	1 and 9

Small demographic group	0.04 (0.00), <0.001	0.38 (0.01), <0.001	1525	0.99	1 and 9
Small demographic group with 50% reduced interaction probability	0.03 (0.00), <0.001	0.22 (0.00), <0.001	3258	1	1 and 9
Education gain 0.05 targeting locals and tourists, forget 0.1					
Large demographic group	0.82 (0.00), <0.001	0.07 (0.00), <0.001	261	0.97	1 and 9
Small demographic group	0.82 (0.00), <0.001	0.07 (0.01), <0.001	70.8	0.89	1 and 9
Small demographic group with 50% reduced interaction probability	0.81 (0.00), <0.001	0.04 (0.01), <0.001	22.3	0.71	1 and 9

Discussion

In this study, we considered the effects of social interactions and information silos in local and tourist populations on social learning about conservation in marine tourism settings. We found that the frequency of interactions between local community members and tourists significantly influenced the accumulation of knowledge within tourist groups. This aligns with social learning theory where diffusion of new information occurs with varying degrees of success based on the social environment (Boyd et al. 2011). Specifically, higher interaction probabilities consistently led to greater knowledge acquisition across all demographic groups, with the relationship between interaction probability and knowledge accumulation being particularly strong (as indicated by high R^2 values in our regression analyses). Even in scenarios where the interaction probability was reduced by 50%, the mean knowledge within smaller tourist groups was only reduced by an average of 43%, suggesting that efficient knowledge transfer still occurred when interactions were less frequent. These results build on existing theories on the role of social learning in natural resource management by providing a more nuanced understanding of how targeted interventions in marine tourism can be fine-tuned to address specific demographic and interactional dynamics, contributing to broader conservation efforts globally (Ardoin et al., 2015, p. 201; Ballantyne et al., 2009; Ballantyne & Packer, 2005; Reed et al., 2010).

The success of conservation education efforts, particularly those aimed at tourists, depends not only on the content of educational programs but also on how these programs are delivered and integrated into existing social networks (Bodin & Crona, 2009; Sterling et al., 2017) . In our model, the selective pressures of social network structure were particularly evident in the presence of information silos, which acted as barriers to social learning. When interactions were frequent, knowledge spread efficiently and reached a greater number of individuals. Conversely in the absence of interactions among demographic groups, social learning was impeded, limiting the amount of conservation knowledge gained by naïve individuals. Our results highlight the importance of social network structures—specifically, how often and with whom individuals interact—in determining the success of educational efforts. This aligns with previous research showing that social networks and strategic community engagement play a critical role in shaping the outcomes of environmental education programs (Bodin & Crona, 2009; Sterling et al., 2017). Programs that encourage more frequent and cross-group interactions are likely to see greater success in disseminating conservation knowledge, leading to more informed and engaged participants.

Conservation efforts often rely on high-impact educational interventions to encourage more sustainable practices among tourists and local communities, particularly when agency resources such as manpower and funding are limited (Baruch-Mordo et al., 2011; Restani & Marzluff, 2002). Our results suggest that even smaller, less frequent interactions can still result in significant knowledge gains, given that these interactions are efficient and focused. This finding supports previous research, which emphasizes that high-quality, purposeful environmental education interactions can have substantial impacts on knowledge retention and behavior change, even when they occur less frequently (Bogner, 1998; Mittelstaedt et al., 1999; Sellmann &

Bogner, 2013). By deliberately enhancing interaction opportunities in more isolated or smaller groups, conservation programs can create environments that favor the spread of knowledge. Future research could evaluate whether characteristics of the individuals involved in the knowledge transfer or specific types of knowledge affect learning and retention. For instance, in cultural evolution, certain ideas or behaviors (i.e., “memes”; Dawkins, 1976) are more likely to be retained and subsequently built upon or adapted over time, similar to natural selection on genetic variation (Creanza et al., 2017). This highlights the importance of tailoring educational interventions to different audience segments, rather than applying a one-size-fits-all approach (Moscardo, 2008).

Additionally, our study emphasizes the need to reach isolated or less-engaged groups of tourists to improve conservation outcomes in marine tourism. For example, targeted educational materials or events tailored to specific demographic groups with known knowledge gaps can be particularly effective (Demnati et al., 2015; Rickinson, 2001). This means that leveraging digital platforms and social media campaigns aimed at younger or less experienced tourists can supplement traditional educational efforts, bridging information gaps and ensuring broader dissemination of conservation messages (Chung et al., 2020; Prensky, 2005; Wilska, 2003). Community-based tourism has also proven effective in engaging isolated communities, while cultural proximity and destination familiarity enhance tourists' connection to conservation efforts (Fafouti et al., 2023; Guan et al., 2022; Prideaux, 2002; Wearing & McDonald, 2002). Furthermore, the spatial design of tourist communities can facilitate the integration of locals and tourists, promoting greater knowledge exchange (Soszyński et al., 2021). Collectively, these findings suggest that policies encouraging cross-group interactions and targeting isolated groups can bridge knowledge gaps, promote sustainable behavior changes, and ensure more effective dissemination of conservation messages across diverse demographics.

The implications of these findings are particularly important in the rapidly growing marine tourism industry, where managing the ecological footprint of tourism is increasingly challenging (Eijgelaar & Peeters, 2024; Gössling et al., 2002; Ortega et al., 2013). As the demand for marine tourism experiences increases, so does the need for targeted and strategic conservation education that engages both tourists and local communities. Our model assumes that the education of the tourist population as a whole will increase over time, because we will have repeated visits to these sites. As a result, educational strategies that account for interaction frequency and reduce information silos between tourists and local communities can significantly enhance conservation messaging. In turn, such behavioral shifts are likely to produce measurable improvements in marine ecosystem protection. Engaging tourists as active participants in conservation—rather than passive observers—represents a transformative opportunity to align the growth of the marine tourism industry with the preservation of marine biodiversity (Beaumont, 2001; Ham & Weiler, 2002).

The insights gained from this study have significant practical applications for outreach education efforts, particularly in coastal regions like Alabama, where marine wildlife conservation is a pressing concern (Alabama Department of Conservation and Natural Resources, 2015). Species such as sea turtles and dolphins, which are critical to the region's biodiversity, have been prioritized in conservation efforts. However, these species continue to face harassment in various Gulf states, often due to inadequate awareness among tourists about responsible wildlife interactions (Duda et al., 2013; Vail, 2016; Williams, 2020). Addressing such issues is essential for protecting federally protected vulnerable species and ensuring the long-term health of marine ecosystems. Our findings suggest that targeted educational strategies—designed with an understanding of local social interactions among demographic groups and existing communication gaps within them—can significantly enhance the effectiveness of conservation messaging. By promoting responsible behaviors among tourists, these programs can mitigate harmful activities and foster greater stewardship of marine wildlife. This aligns with broader research emphasizing the need for locally tailored conservation efforts to maximize impact (Cinner & Aswani, 2007).

Finally, our findings suggest that conservation education should focus not only on increasing interaction frequency but also on improving the quality of these interactions. Future research could explore which types of interactions most effectively promote conservation behaviors. For example, understanding how personalized or interactive educational experiences compare to passive forms of information dissemination, such as pamphlets or signage, could help optimize conservation efforts in tourism settings. By fostering more efficient social learning and targeted educational interventions, tourism operators and policy-makers can align conservation efforts with industry growth, ensuring the long-term sustainability of marine ecosystems.

Conclusions

This study provides insights into the role of information flow through social learning in shaping the effectiveness of conservation education, particularly in marine tourism settings. By using an agent-based model, we demonstrated that both the frequency of interactions and the presence of information silos significantly influence how conservation knowledge is disseminated among tourists. Our findings highlight the importance of designing educational interventions that not only increase interaction opportunities but also strategically target isolated groups to ensure that knowledge is spread more evenly across all demographic segments.

Acknowledgements

This research was partially funded by the Auburn Agricultural Research Station and the National Institute of Food and Agriculture Hatch Program 1025651.

Literature Cited

Adams, B. N. (1967). Interaction Theory and the Social Network. *Sociometry*, *30*(1), 64–78. https://doi.org/10.2307/2786439

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alabama Department of Conservation and Natural Resources. (2015). *Alabama's Wildlife Action Plan 2015-2025*. https://www.outdooralabama.com/sites/default/files/Research/SWCS/AL_SWAP_FINAL%20June2017.pdf

Allen, W., Bosch, O., Kilvington, M., Harley, D., & Brown, I. (2001). Monitoring and adaptive management: Resolving social and organisational issues to improve information sharing in natural resource management. *Natural Resources Forum*, *25*(3), 225–233. https://doi.org/10.1111/j.1477-8947.2001.tb00764.x

Ardoin, N. M., Wheaton, M., Bowers, A. W., Hunt, C. A., & Durham, W. H. (2015). Nature-based tourism's impact on environmental knowledge, attitudes, and behavior: A review and analysis of the literature and potential future research. *Journal of Sustainable Tourism*, *23*(6), 838–858. https://doi.org/10.1080/09669582.2015.1024258

Badalamenti, F., Espla, A. A., Voultsiadou, E., Sánchez Lizaso, J., D'Anna, G., Pipitone, C., Mas, J., FERNANDEZ, J. A., Whitmarsh, D., & Riggio, S. (2000). Cultural and Socio-Economic Impacts of Mediterranean Marine Protected Areas. *Environmental Conservation*, *27*, 110–125. https://doi.org/10.1017/S0376892900000163

Ballantyne, R., & Packer, J. (2005). Promoting environmentally sustainable attitudes and behaviour through free-choice learning experiences: What is the state of the game? *Environ Educ Res*, *11*. https://doi.org/10.1080/13504620500081145

Ballantyne, R., Packer, J., & Falk, J. (2011). Visitors learning for environmental sustainability: Testing short- and long-term impacts of wildlife tourism experiences using structural equation modelling. *Tourism Management*, *32*. https://doi.org/10.1016/j.tourman.2010.11.003

Ballantyne, R., Packer, J., & Hughes, K. (2009). Tourists' support for conservation messages and sustainable management practices in wildlife tourism experiences. *Tourism Management*, *30*(5), 658–664. https://doi.org/10.1016/j.tourman.2008.11.003

Bandura, A. (1977). *Social learning theory* (pp. viii, 247). Prentice-Hall.

Baruch-Mordo, S., Breck, S. W., Wilson, K. R., & Broderick, J. (2011). The Carrot or the Stick? Evaluation of Education and Enforcement as Management Tools for Human-Wildlife Conflicts. *PLoS ONE*, *6*(1), e15681. https://doi.org/10.1371/journal.pone.0015681

Beaumont, N. (2001). Ecotourism and the Conservation Ethic: Recruiting the Uninitiated or Preaching to the Converted? *Journal of Sustainable Tourism*, *9*(4), 317–341. https://doi.org/10.1080/09669580108667405

Bento, F., Tagliabue, M., & Lorenzo, F. (2020). Organizational Silos: A Scoping Review Informed by a Behavioral Perspective on Systems and Networks. *Societies*, *10*(3), Article 3. https://doi.org/10.3390/soc10030056

Bisack, K. D., & Clay, P. M. (2020). Compliance with marine mammal protection: Focus groups reveal factors in commercial fishermen's decisions. *Marine Policy*, *115*, 103789. https://doi.org/10.1016/j.marpol.2019.103789

Bodin, Ö., & Crona, B. I. (2009). The role of social networks in natural resource governance: What relational patterns make a difference? *Global Environmental Change*, *19*(3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002

Bogner, F. X. (1998). The Influence of Short-Term Outdoor Ecology Education on Long-Term Variables of Environmental Perspective. *The Journal of Environmental Education*, *29*(4), 17–29. https://doi.org/10.1080/00958969809599124

Boyd, R., Richerson, P. J., & Henrich, J. (2011). The cultural niche: Why social learning is essential for human adaptation. *Proceedings of the National Academy of Sciences*, *108*(supplement_2), 10918–10925. https://doi.org/10.1073/pnas.1100290108

Burger, J. (2000). Landscapes, tourism, and conservation. *Science of The Total Environment*, *249*(1), 39–49. https://doi.org/10.1016/S0048-9697(99)00509-4

Cheung, L. T. O., & Fok, L. (2014). Assessing the Role of Ecotourism Training in Changing Participants' Pro-Environmental Knowledge, Attitude and Behaviour. *Asia Pacific Journal of Tourism Research*, *19*(6), 645–661. https://doi.org/10.1080/10941665.2013.797003

Chung, C.-H., Chiu, D. K. W., Ho, K. K. W., & Au, C. H. (2020). Applying social media to environmental education: Is it more impactful than traditional media? *Information Discovery and Delivery*, *48*(4), 255–266. https://doi.org/10.1108/IDD-04-2020-0047

Cinner, J. E., & Aswani, S. (2007). Integrating customary management into marine conservation. *Biological Conservation*, *140*(3), 201–216. https://doi.org/10.1016/j.biocon.2007.08.008

Creanza, N., Kolodny, O., & Feldman, M. W. (2017). Cultural evolutionary theory: How culture evolves and why it matters. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(30), 7782. https://doi.org/10.1073/pnas.1620732114

Davtian, A., Shabalina, O., Sadovnikova, N., Berestneva, O., & Parygin, D. (2022). Principles for Modeling Information Flows in Open Socio-Economic Systems. In A. G. Kravets, A. A. Bolshakov, & M. Shcherbakov (Eds.), *Society 5.0: Human-Centered Society Challenges and Solutions* (pp. 167–173). Springer International Publishing. https://doi.org/10.1007/978-3-030-95112-2_14

De Souza, R. C. F., Ramos, M. A., De Albuquerque, U. P., Souto, A., & Schiel, N. (2022). Visitors' perception when participating in a poorly planned ecotourism activity: The case of dolphin watching in Northeastern Brazil. *Journal of Ecotourism*, *21*(3), 197–209. https://doi.org/10.1080/14724049.2021.1929260

Demnati, F., Allache, F., & Ernoul, L. (2015). Population typology to better target environmental education: A case from Algeria. *Environment, Development and Sustainability*, *17*(2), 331–339. https://doi.org/10.1007/s10668-015-9647-9

Duda, M. D., Beppler, T., & Horstman, S. C. (2013). Attitudes Toward Illegal Feeding and Harassment of Wild Dolphins in Panama City. *Human Dimensions of Wildlife*, *18*(3), 236–238. https://doi.org/10.1080/10871209.2013.762566

Dwyer, L. (2018). Emerging Ocean Industries: Implications for Sustainable Tourism Development. *Tourism in Marine Environments*, *13*(1), 25–40. https://doi.org/10.3727/154427317X15018194204029

Eijgelaar, E., & Peeters, P. (2024). The Global Footprint of Tourism. In *The Wiley Blackwell Companion to Tourism* (pp. 533–547). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119753797.ch36

Fabian, M. C., Cook, A., & Old, J. M. (2020). Do Australians have the willingness to participate in wildlife conservation? *Australian Zoologist*, 575–584. https://doi.org/10.7882/AZ.2019.010

Fafouti, A. E., Vythoulka, A., Delegou, E. T., Farmakidis, N., Ioannou, M., Perellis, K., Giannikouris, A., Kampanis, N. A., Alexandrakis, G., & Moropoulou, A. (2023). Designing Cultural Routes as a Tool of Responsible Tourism and Sustainable Local Development in Isolated and Less Developed Islands: The Case of Symi Island in Greece. *Land*, *12*(8), Article 8. https://doi.org/10.3390/land12081590

Gilchrist, G., Mallory, M., & Merkel, F. (2005). Can Local Ecological Knowledge Contribute to Wildlife Management? Case Studies of Migratory Birds. *Ecology and Society*, *10*(1). https://www.jstor.org/stable/26267752

Gössling, S., Hansson, C. B., Hörstmeier, O., & Saggel, S. (2002). Ecological footprint analysis as a tool to assess tourism sustainability. *Ecological Economics*, *43*(2), 199–211. https://doi.org/10.1016/S0921-8009(02)00211-2

Guan, J., Chan, J. H., Bi, J., & Qi, X. (2022). Cultural proximity, destination familiarity and tourists' sense of away-from-home (SAFH). *Journal of Destination Marketing & Management*, *23*, 100670. https://doi.org/10.1016/j.jdmm.2021.100670

Ham, S., & Weiler, B. (2002). Interpretation as the centrepiece of sustainable wildlife tourism. *Sustainable Tourism: A Global Perspective*, 35–44.

Hardiman, N., & Burgin, S. (2010). Recreational impacts on the fauna of Australian coastal marine ecosystems. *Journal of Environmental Management*, *91*(11), 2096–2108. https://doi.org/10.1016/j.jenvman.2010.06.012

Harriott, V. J. (2004). Marine Tourism Impacts on the Great Barrier Reef. *Tourism in Marine Environments*, *1*(1), 29–40. https://doi.org/10.3727/154427304774865850

Jacobson, S. K., & Robles, R. (1992). Ecotourism, sustainable development, and conservation education: Development of a tour guide training program in Tortuguero, Costa Rica. *Environmental Management*, *16*(6), 701–713. https://doi.org/10.1007/BF02645660

Keane, A., Ramarolahy, A. A., Jones, J. P. G., & Milner-Gulland, E. j. (2011). Evidence for the effects of environmental engagement and education on knowledge of wildlife laws in Madagascar. *Conservation Letters*, *4*(1), 55–63. https://doi.org/10.1111/j.1755-263X.2010.00144.x

Kleespies, M. W., Feucht, V., Becker, M., & Dierkes, P. W. (2022). Environmental Education in Zoos—Exploring the Impact of Guided Zoo Tours on Connection to Nature and Attitudes towards Species Conservation. *Journal of Zoological and Botanical Gardens*, *3*(1), Article 1. https://doi.org/10.3390/jzbg3010005

Lee, T. H., Jan, F.-H., & Chen, J.-C. (2023). Influence analysis of interpretation services on ecotourism behavior for wildlife tourists. *Journal of Sustainable Tourism*, *31*(5), 1233–1251. https://doi.org/10.1080/09669582.2021.1949016

Lück, M. (2015). Education on marine mammal tours – But what do tourists want to learn? *Ocean & Coastal Management*, *103*, 25–33. https://doi.org/10.1016/j.ocecoaman.2014.11.002

Ma, H., Papworth, S. K., Qian, J., & Turvey, S. T. (2022). The medium over the message: Differential knowledge of conservation outreach activities and implications for threatened species. *Journal of Environmental Management*, *310*, 114716. https://doi.org/10.1016/j.jenvman.2022.114716

Mallory, M. L., Fontaine, A. J., Akearok, J. A., & Johnston, V. H. (2006). Synergy of local ecological knowledge, community involvement and scientific study to develop marine wildlife areas in eastern Arctic Canada. *Polar Record*, *42*(3), 205–216. https://doi.org/10.1017/S0032247406005481

Masud, M. M., Aldakhil, A. M., Nassani, A. A., & Azam, M. N. (2017). Community-based ecotourism management for sustainable development of marine protected areas in Malaysia. *Ocean & Coastal Management*, *136*, 104–112. https://doi.org/10.1016/j.ocecoaman.2016.11.023

Medio, D., Ormond, R. F. G., & Pearson, M. (1997). Effect of briefings on rates of damage to corals by scuba divers. *Biological Conservation*, *79*(1), 91–95. https://doi.org/10.1016/S0006-3207(96)00074-2

Miller, M. L. (1993). The rise of coastal and marine tourism. *Ocean & Coastal Management*, *20*(3), 181–199. https://doi.org/10.1016/0964-5691(93)90066-8

Mittelstaedt, R., Sanker, L., & VanderVeer, B. (1999). Impact of a Week-Long Experiential Education Program on Environmental Attitude and Awareness. *Journal of Experiential Education*, *22*(3), 138–148. https://doi.org/10.1177/105382599902200306

Mixon, J. (2008). Linguistic Silos as Barriers to Sustainable Environment. *Tulsa Law Review*, *44*, 7.

Moscardo, G. (2008). Building community capacity for tourism development: Conclusions. *Building Community Capacity for Tourism Development*, 172–179.

O'Bryhim, J. R., & Parsons, E. C. M. (2015). Increased knowledge about sharks increases public concern about their conservation. *Marine Policy*, *56*, 43–47. https://doi.org/10.1016/j.marpol.2015.02.007

Olsson, P., & Folke, C. (2001). Local Ecological Knowledge and Institutional Dynamics for Ecosystem Management: A Study of Lake Racken Watershed, Sweden. *Ecosystems*, *4*, 85–104. https://doi.org/10.1007/s100210000061

Orams, M. (1998). *Marine Tourism: Development, Impacts and Management*. Routledge. https://doi.org/10.4324/9780203197110

Orams, M. B. (1997). The effectiveness of environmental education: Can we turn tourists into "greenies"? *Progress in Tourism and Hospitality Research*, *3*(4), 295–306. https://doi.org/10.1002/(SICI)1099-1603(199712)3:4<295::AID-PTH85>3.0.CO;2-D

Orams, M. B., & Hill, G. J. E. (1998). Controlling the Ecotourist in a Wild Dolphin Feeding Program: Is Education the Answer? *The Journal of Environmental Education*, *29*(3), 33–38. https://doi.org/10.1080/00958969809599116

Ortega, J. L. C., Dagostino, R. M. C., & Massam, B. H. (2013). Sustainable Tourism: Whale Watching Footprint in the Bahía de Banderas, México. *Journal of Coastal Research*, *29*(6), 1445–1451. https://doi.org/10.2112/JCOASTRES-D-12-00213.1

Pino, A. L. (2023). *3: Breaking the Silos: Science Communication for Everyone*. https://bristoluniversitypressdigital.com/edcollchap/book/9781529226829/ch003.xml

Prell, C., Reed, M., Racin, L., & Klaus, H. (2010). Competing Structure, Competing Views: The Role of Formal and Informal Social Structures in Shaping Stakeholder Perceptions. *Ecology and Society*, *15*. https://doi.org/10.5751/ES-03652-150434

Prensky, M. (2005). What Can You Learn from a Cell Phone? Almost Anything! *Innovate: Journal of Online Education*, *1*(5). https://www.learntechlib.org/p/107282/

Prideaux, B. (2002). Building visitor attractions in peripheral areas—Can uniqueness overcome isolation to produce viability? *International Journal of Tourism Research*, *4*(5), 379–389. https://doi.org/10.1002/jtr.387

R Core Team. (2023). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Railsback, S. F., & Grimm, V. (2019). *Agent-based and individual-based modeling: A practical introduction* (Second edition). Princeton University Press.

Reed, M., Evely, A., Cundill, G., Fazey, I., Glass, J., Laing, A., Newig, J., Parrish, B., Prell, C., Raymond, C., & Stringer, L. (2010). What is Social Learning? *ECOLOGY AND SOCIETY*, *15*, r1. https://doi.org/10.5751/ES-03564-1504r01

Restani, M., & Marzluff, J. M. (2002). Funding Extinction? Biological Needs and Political Realities in the Allocation of Resources to Endangered Species Recovery: An existing priority system, which should guide the Fish and Wildlife Service in endangered species recovery, is ineffective, and current spending patterns decrease long-term viability of island species. *BioScience*, *52*(2), 169–177. https://doi.org/10.1641/0006-3568(2002)052[0169:FEBNAP]2.0.CO;2

Rickinson, M. (2001). Learners and Learning in Environmental Education: A critical review of the evidence. *Environmental Education Research*, *7*(3), 207–320. https://doi.org/10.1080/13504620120065230

Rist, S., Chidambaranathan, M., Escobar, C., Wiesmann, U., & Zimmermann, A. (2007). Moving from sustainable management to sustainable governance of natural resources: The role of social learning processes in rural India, Bolivia and Mali. *Journal of Rural Studies*, *23*(1), 23–37. https://doi.org/10.1016/j.jrurstud.2006.02.006

Rogers, E. M. (2003). *Diffusion of innovations* (Fifth edition, Free Press trade paperback edition). Free Press.

Rossing, B. E. (1991). Patterns of informal incidental learning: Insights from community action. *International Journal of Lifelong Education*, *10*(1), 45–60. https://doi.org/10.1080/0260137910100105

Salm, R. V. (1985). Integrating Marine conservation and tourism. *International Journal of Environmental Studies*, *25*(4), 229–238. https://doi.org/10.1080/00207238508710231

Scheyvens, R. (1999). Ecotourism and the empowerment of local communities. *Tourism Management*, *20*(2), 245–249. https://doi.org/10.1016/S0261-5177(98)00069-7

Sellmann, D., & Bogner, F. X. (2013). Effects of a 1-day environmental education intervention on environmental attitudes and connectedness with nature. *European Journal of Psychology of Education*, *28*(3), 1077–1086. https://doi.org/10.1007/s10212-012-0155-0

Sherchan, W., Nepal, S., & Paris, C. (2013). A survey of trust in social networks. *ACM Comput. Surv.*, *45*(4), 47:1-47:33. https://doi.org/10.1145/2501654.2501661

Soszyński, D., Sowińska-Świerkosz, B., Stokowski, P. A., & Tucki, A. (2021). Spatial arrangements of tourist villages: Implications for the integration of residents and tourists. In *Tourism Spaces*. Routledge.

Sterling, E. J., Filardi, C., Toomey, A., Sigouin, A., Betley, E., Gazit, N., Newell, J., Albert, S., Alvira, D., Bergamini, N., Blair, M., Boseto, D., Burrows, K., Bynum, N., Caillon, S., Caselle, J. E., Claudet, J., Cullman, G., Dacks, R., … Jupiter, S. D. (2017). Biocultural approaches to well-being and sustainability indicators across scales. *Nature Ecology & Evolution*, *1*(12), 1798–1806. https://doi.org/10.1038/s41559-017-0349-6

Toderi, M., Powell, N., Seddaiu, G., Roggero, P. P., & Gibbon, D. (2007). Combining social learning with agro-ecological research practice for more effective management of nitrate pollution. *Environmental Science & Policy*, *10*(6), 551–563. https://doi.org/10.1016/j.envsci.2007.02.006

Vail, C. S. (2016). An Overview of Increasing Incidents of Bottlenose Dolphin Harassment in the Gulf of Mexico and Possible Solutions. *Frontiers in Marine Science*, *3*. https://doi.org/10.3389/fmars.2016.00110

Wang, H., & Wellman, B. (2010). Social Connectivity in America: Changes in Adult Friendship Network Size From 2002 to 2007. *American Behavioral Scientist*, *53*(8), 1148–1169. https://doi.org/10.1177/0002764209356247

Watkins, K. E., & Marsick, V. J. (1992). Towards a theory of informal and incidental learning in organizations∗. *International Journal of Lifelong Education*, *11*(4), 287–300. https://doi.org/10.1080/0260137920110403

Wearing, S., & McDonald, M. (2002). The Development of Community-based Tourism: Re-thinking the Relationship Between Tour Operators and Development Agents as

Intermediaries in Rural and Isolated Area Communities. *Journal of Sustainable Tourism*, *10*(3), 191–206. https://doi.org/10.1080/09669580208667162

Williams, D. (2020, July 27). Sea turtles harassed on Alabama beaches as nest numbers tumble. *WKRG News 5*. https://www.wkrg.com/top-stories/sea-turtles-harassed-on-alabama-beaches-as-nest-numbers-tumble/

Wilska, T.-A. (2003). Mobile Phone Use as Part of Young People's Consumption Styles. *Journal of Consumer Policy*, *26*(4), 441–463. https://doi.org/10.1023/A:1026331016172

Zeppel, H., & Muloin, S. (2008). Conservation Benefits of Interpretation on Marine Wildlife Tours. *Human Dimensions of Wildlife*, *13*(4), 280–294. https://doi.org/10.1080/10871200802187105